



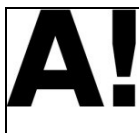
**Aalto University**  
**School of Business**

# **Dynamic Pricing in the Hair & Beauty Industry**

Case Timma

Bachelor's Thesis  
Lari Mykrä  
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 <b>Aalto University School of Business</b>	Aalto University, P.O. BOX 11000, 00076 AALTO <a href="http://www.aalto.fi">www.aalto.fi</a> <b>Abstract of bachelor's thesis</b>
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**Author** Lari Mykrä

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### Abstract

Dynamic pricing has become increasingly popular especially on electronic marketplaces with the help of the rise of modern computer systems. Essentially a form of price discrimination and a means of revenue management and maximization, dynamic pricing has been most widely studied and used in the air travel and hospitality industries. In the very core, dynamic pricing is based on being able to accurately estimate demand for a certain product or service. Electronic marketplaces make demand forecasting easier for businesses in many cases, so dynamic pricing becomes possible for a variety of industries.

In my thesis I have studied different factors that affect the probability of sale of a certain time slot in a marketplace selling appointments for hair & beauty services. The research data consists of 62 137 available time slots during the month of November 2017. The data was analyzed in R and a Generalized Linear Model (GLM) with a binomial variance function and a logit link function was fitted to study regressions. My research proves that time of day, proximity to center, consumer ratings and weekday all have a statistically significant effect on whether a particular time slot is sold or not.

The results concerning the effect of consumer ratings and proximity to center (location) are in alignment with previous research from the hospitality industry. The effect of time of day or weekday on the likelihood of sale had not been researched before in a relevant industry.

It seems that to develop a deeper understanding of the factors affecting likelihood of sale and thus demand in the hair & beauty industry more variables would have to be taken into account. This seems like a feasible subject for further research. Also, a similar study from a different service-based industry would be interesting.

**Keywords** dynamic pricing, hair & beauty, electronic marketplace

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# **1 Introduction**

Electronic marketplaces that gather sellers and willing buyers of a particular product or service in the same virtual location have been trending massively over the course of the past decade. Examples from various industries such as Hotels.com, Supersaver, Trivago, eBay, Airbnb, Foodora or Venuu make it easier for sellers and buyers to meet, make pricing more transparent and remove unnecessary friction from the transaction processes. These kinds of platforms almost always live off commissions from transactions made via the platform, so it is in the interest of the companies running these platforms to streamline every aspect of their service to maximize revenues of the supply-side participants.

On the other hand, every participating seller (company or individual) is likely looking to maximize their own sales. In many cases the answer to doing this is dynamic pricing, a form of price discrimination. In essence, dynamic pricing is the concept of automatically changing the price of a product/service based on estimated demand at different price points to maximize profits.

The concept of dynamic pricing first became popular in the airline industry in the 1970s along with the deregulation of the industry. Another major industry benefiting from the use of dynamic pricing is the hospitality industry. New applications of dynamic pricing are found constantly in different industries as technology and algorithms making dynamic pricing possible become available more easily and with a cheaper price tag.

## **1.1 Background and Scope of the Study**

To develop a functioning dynamic pricing model or algorithm requires deep understanding of a certain market and the factors affecting demand in the market. A case study from the hair & beauty industry (hair and beauty salons) will shed light on if it could be a line of business suitable for dynamic pricing of services.

The salon industry consists of the hair, beauty and massage sectors. In Finland the value of the salon industry is estimated to be roughly a billion euros yearly whereas in Europe the estimated value is 100 billion euros yearly. This entails products and services sold through salons. Still, surprisingly little research has been made concerning the industry.

Although the salon industry as a whole is quite large based on revenues, individual salons are small (on average 1.8 people work in a single salon) and there are few chains. In other words, the market is very fragmented as the estimated number of companies operating in the space in Finland is around 20 000. It is noted, however, that in many cases two or more companies or sole proprietors operate in the same salon.

## **1.2 Research Problem and Questions**

The main purpose of this research is to review the theory on the subject of dynamic pricing and to find out which factors would have to be taken into account when developing a model for dynamic pricing of hair and beauty services.

The aim of this study is to familiarize the reader with the concept of dynamic pricing and its most common applications in electronic commerce. Also, a case study of a marketplace selling hairdressing & beauty appointments is conducted. I aim to answer the following questions:

- Do certain factors (location of salon, time of day, consumer reviews) affect the probability of sale of a certain time available?
- Would dynamic pricing be feasible for these services on the marketplace?

It is not, however, within the scope of this study to formulate a dynamic pricing model or algorithm for these services.

## **1.3 Outline of the Research**

In the literature review chapter principles and theory behind dynamic pricing are discussed. Different angles and views of dynamic pricing are evaluated, such as which factors make a particular service or product especially suitable to being priced dynamically. Attention is also given to how consumers perceive the use of dynamic pricing and whether it affects their view on a marketplace or brand.

In the third chapter the case company Timma is presented. Also, the research method and research design are discussed in more detail to familiarize the reader with how the data collection and research of the case company was performed.

A case study will then be conducted to identify different factors that distinguish various service providers from one another and to test whether the effect of these factors on the probability of sale on the Timma –platform is statistically significant.

Finally, findings are discussed, as well as implications to practice and research. Also suggestions for further research are made.

## **2 Literature Review**

### **2.1 Dynamic Pricing as a Concept**

As defined by Pigou (1932), there are three degrees of price discrimination. First-degree price discrimination occurs when a company charges the maximum possible price for each unit consumed and thus is able to capture all available consumer surplus. In reality this rarely happens. Second-degree price discrimination happens when a different price is charged for different quantities of a product or service consumed. This is quite common e.g. when giving bulk discounts on a product. Third-degree price discrimination means charging different prices from different consumer groups. Examples include pricing movie tickets differently for children, adults and seniors or giving student discounts from software purchased online. Dynamic pricing is a form of third-degree price discrimination (Krugmann, 2000), where the price can be changed automatically based on remaining inventory and estimated future demand (Elmaghraby & Keskinocak, 2003). (Pigou, 1932)

#### **2.1.1 Overview of Dynamic Pricing**

Dynamic pricing as a means of price discrimination has gained popularity with the help of the rise of modern computer systems. While no single researcher or group of researchers are recognized as inventing the concept of dynamic pricing, in their 1963 article Kincaid & Darling (1963) were among the first ones to study an inventory pricing problem, where the optimal solution was to use dynamic pricing to maximize expected total revenues. Furthermore, Lovelock (1984) argues that perishable goods are especially suitable to be dynamically priced. Since services are perishable by nature, dynamic pricing would be an optimal solution for service pricing. Of course, as Lovelock (1984) further explains, the demand curve and price elasticity of a

service must be known in order for dynamic pricing to be optimal. Jayaraman & Baker (2003) take Lovelock's findings a bit further and argue that perishable services such as hotel rooms and air travel are optimal for dynamic pricing for five reasons:

1. Not possible to store or keep inventory
2. Possible to class and price differentially (e.g. different rates for different consumer segments)
3. Centralized order processing eases estimating supply and demand
4. Value differential between incremental value and incremental cost is high
5. Changes in demand can be sudden and temporary

Today, applications of dynamic pricing can be found from various industries, but it is most used and researched in the airline and hospitality industries.

In essence, dynamic pricing means being able to determine the price of a product or service based on estimated demand to maximize revenue or profits (Elmaghraby & Keskinocak, 2003). If the demand of a product or service is known or can be reliably estimated, prices can be set in a way that maximizes estimated profits. Alternatively, Kannan & Kopalle (2001) determine dynamic pricing as a "pricing strategy in which prices change over time, across consumers or across product/service bundles".

Regardless of how it's determined, to reach the optimal solution for any dynamic pricing problem the demand curve for the product/service in question must be known. Besbes & Zeevi (2009) argue that this rarely is the case in real life and develop a model for solving dynamic pricing problems without knowing the demand function.

### **2.1.2 Use Cases of Dynamic Pricing**

Burger & Fuchs (2005) studied dynamic pricing in the context of the airline industry. They found that "a dynamic pricing strategy has a neutral or a positive effect on revenues, depending on competitors' revenue management strategy". Traditionally airlines have tackled the price discrimination problem with seat inventory control, booking-limit calculations and e.g. minimum stay requirements. Burger & Fuchs (2005) found that dynamic pricing works especially well against these traditional revenue management methods. However, if two (or more) competing airlines would apply

dynamic pricing they would dynamically start to undercut each others' prices which would in turn likely result in having a neutral total effect on demand. (Burger & Fuchs, 2005)

Abrate et al. (2012) studied the use of dynamic pricing in the context of the European hotel industry. Their research consisted of data from some 1000 hotels in eight capital cities in Europe. According to their findings, over 90% of prices changed during their test period suggesting that at least some form of dynamic pricing was performed by a vast majority of the hotels studied. Furthermore, in almost half of the cases the prices observed changed by more than 10%, meaning that savvy consumers could get significant savings. It is noted, however, that price fluctuations are smaller than in the airline industry. It is also shown that whether prices go up or down when getting closer to the date of the booking depends on a variety of factors such as star-rating, the weekday for which the room is booked and the overall demand situation in the city in question. (Abrate et al., 2012)

Dynamic pricing also has its applications in more traditional industries, such as retail. Jayaraman & Baker (2003) argue that “dynamic pricing is best suited for products that are clearly specified or widely understood, that are either perishable (consumables) or time-sensitive (hotel rooms) or have a depreciating value (e.g. computer components, automotive parts)”. Elmaghraby & Keskinocak (2003) studied dynamic pricing in the context of products where inventory restrictions apply. They argue, that e.g. fashion goods, which arguably fit into the category of having depreciating value, are in many cases suitable to be priced dynamically. The life cycle of fashion items is usually short, thus making inventory replenishments hard or impossible for retailers, so they can in a way be considered perishables similar to e.g. hotel rooms. (Elmaghraby & Keskinocak, 2003)

### 2.1.3 Customer Perceptions on Dynamic Pricing

Dynamic pricing has been proven to be effective a means for revenue management on the supply side, but how do consumers feel about ever-changing prices? Kannan & Kopalle (2001) argue, that the trustworthiness of a vendor is negatively affected if consumers realize they have ended up paying more because of dynamic pricing. The key to retaining customers' trust is making dynamic pricing structures transparent. An



example of this is giving discounts to loyal customers or frequent shoppers, since most customers understand the logic behind this and accept it. (Kannan & Kopalle, 2001)

Haws & Bearden (2006) continue on the subject, confirming in their study that it is indeed the differences in pricing between customers that result in the greatest perceptions of unfairness. Also, price changes within very short periods of time are viewed as more unfair than changes during a longer period. If the change in price has occurred over a period of one month, fairness perceptions aren't affected anymore. (Haws & Bearden, 2006)

## **2.2 Differences between Electronic Marketplaces**

The concept of homogeneous versus heterogeneous supply marketplace was coined by Golden (2017). While the publication is not scientific, the classification very well illustrates key differences between electronic marketplaces. Golden (2017) categorizes electronic marketplaces based on homogeneity or heterogeneity of supply.

Homogeneity of supply means that a certain supplier's product or service is not easily distinguishable from the product or service of another. This is the case for example with Uber. In heterogeneous marketplaces on the other hand, such as Airbnb, the supply is unique and distinguishable from each other. Moreover, Golden (2017) argues, that heterogeneous supply marketplaces are search marketplaces, where one of the greatest transaction barriers for the consumer is deciding the right supply, whereas homogeneous supply marketplaces are matching marketplaces that mostly have to worry about making the transaction as smooth as possible for the consumer. (Golden, 2017)

As previously discussed, dynamic pricing is best suitable for goods or services that are perishable, time-sensitive or have a depreciating value (Jayaraman & Baker, 2003). However, as Elmaghraby & Keskinocak (2003) argue, if demand can be reliably estimated, dynamic pricing can be effectively used to maximize profits. This, in turn, means that dynamic pricing could be suitable and effective for any electronic marketplace or a company selling its goods or services via an electronic marketplace if only demand can be forecast on a reliable enough level.

Generally dynamic pricing in its automated form is better suitable for marketplaces where the size of the companies providing the supply is large (e.g. flights) than for marketplaces where the supply is mostly provided by small companies (e.g. Airbnb), since creating a dynamic pricing algorithm requires a deep understanding of demand data (Jayaraman & Baker, 2003) and is quite likely very expensive. This could, however, be solved by Airbnb and its likes offering “Dynamic Pricing as a Service”, where the marketplace provider would offer a dynamic pricing algorithm for the supply to use.

## **2.3 Limitations of Dynamic Pricing on Electronic Marketplaces**

While dynamic pricing seems to be widely accepted as a suitable means for maximizing revenues on electronic marketplaces, some limitations should be considered. A downward spiraling price war situation, an escalation of the airline example from chapter 2.1.2 can be explained as Bertrand’s paradox (1903). If a competitor reduces prices a company is tempted to reduce its own prices even more. This will result in both companies ending up on the lowest set price level. Because of this, lower limits for prices need to be set in dynamic pricing algorithms if they are competing against each other.

Also, as mentioned before, dynamic pricing is essentially based on being able to estimate the future demand of a product or service. For a company like Uber operating a homogenous supply marketplace where it completely controls the supply this is reasonably easy. Therefore it makes sense for Uber to use their surge pricing. A company running a heterogeneous supply marketplace, like Airbnb, might have an equally good estimate of future demand. However, they are not allowed to dynamically price vacation homes listed on the site without the permission of the homeowners. Airbnb could offer dynamic pricing for venues listed on the marketplace, but the algorithm would have to be created by Airbnb since it is not feasible for most venue providers to formulate a dynamic pricing algorithm themselves, as mentioned before.

## **3 Methodology**

### **3.1 Case Selection and Introduction**

Normally appointments in the hair, beauty and massage industries are booked on the phone or via online booking on the business' own website. The Timma-marketplace provides an additional booking and marketing channel, where professionals working in the industries can market their available times for up to five following days. These times are at a high risk for being left empty and thus producing zero revenues. Timma aims to solve this inefficiency by gathering the times and customers looking for last-minute times to the same platform. Additionally, Timma makes it easier for consumers to browse through businesses near their location and compare prices, reviews and available times. When a consumer makes a booking, she is forced to pay in advance to minimize the amounts of no-shows. Consumers are often willing to do this, since most of the times sold on the platform are discounted.

### **3.2 Data Collection**

Case data was gathered from Timma Oy's Timma.fi –marketplace sales in Helsinki over the period of one full month, November 2017. According to the company there is some seasonal variation in the sales within the month, so it is important to study the data from a whole month's period. This seasonal variation is caused by e.g. paydays in Finland usually being the 15<sup>th</sup> and 30<sup>th</sup> days of the month.

A data set of 62 137 total available time slots was studied. The amount of appointments sold during the month was 6 308. It is important to note, however, that an available time slot can be for example four hours long and a sold appointment is usually between half an hour and two and a half hours long. This means that it is not possible to estimate the percentage of sold appointments from all available time slots only with this data.

### **3.3 Research Method**

Generalized linear model (GLM) was used to analyze the regressions between different factors and their effect on the likelihood of sale of a certain time slot. It is important to

note, however, that GLMs reveal the correlations between different variables but correlation does not necessarily imply causality.

Generalized linear models were introduced by Nelder & Wedderburn (1972). GLMs make it possible to model non-normal data when usual assumptions used in regression models are not satisfied. Generalized linear models consist of a positive variance function and a monotonic link function. The variance function describes the varying of the response as a function of the mean while the link function transforms the mean to a scale, making the model linear. (Nelder & Wedderburn, 1972)

## 4 Case Study: Timma – Marketplace for Hair & Beauty

### 4.1 Structuring the Data

The data obtained from the company was divided into two spreadsheets, available times and sold times. The column headers of available times and sold times are shown in Figures 1 and 2 respectively. The meanings of the headers are shown in Figure 3.

start	end	customerName	rating	createdTime	postalCode
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Figure 1. Headers of available times table.

start	end	customerName	rating	purchaseTime	postalCode
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Figure 2. Headers of sold times table.

Header	Meaning
start	starting time of sold or available slot
end	ending time of sold or available slot
customerName	name of the salon where the time is available or sold
rating	customer rating of the salon, 1 to 5 stars

createdTime	time when available slot was created
purchaseTime	time when the purchase was made
postalCode	postal code of the salon

*Figure 3. Meanings of headers from available and sold times tables.*

Based on this information, two additional columns were created to help analyze the data better. Same three columns were added into both data sets. Headers and meanings are shown in Figure 4.

Header	Meaning
timeOfDay	morning, day, afternoon or evening
proximityToCenter	downtown, closeby or outside

*Figure 4. Meanings of headers of new columns added.*

Time of day was divided into morning, day, afternoon and evening based on the starting time of the available or sold time slot. 06:00 – 09:45 is morning, 10:00 – 13:45 is day, 14:00 – 16:45 is afternoon and 17:00 – 21:00 is evening.

Proximity to center means (quite self-explanatorily) the closeness of a salon to Helsinki city center. Proximity to center was divided into three categories, downtown, closeby and outside. Basically the most densely populated areas such as Kamppi, Punavuori and Kallio are categorized as downtown, district centers such as Vuosaari or Lauttasaari are categorized as closeby and the remaining areas, such as Paloheinä or Etelä-Haaga are categorized as outside.

## 4.2 Formulating the Hypotheses

It would seem logical that a salon in a densely populated area would be likely to sell more than a salon in the outskirts of the city. Also, a salon with a high customer rating should sell more than a salon with a lower rating, since ratings are a form of online

word of mouth and generally better word of mouth leads to more sales (Chevalier & Mayzlin, 2006). Most people are working during the day, so an available time in the afternoon or evening could perhaps be preferable for many.

Ögut & Tas (2012) proved that in the context of the hotel industry, a higher customer rating significantly increases online sales. The effect of location on hotel selection has been researched by Rivers et al. (1991) and Ananth et al. (1992). Both found that convenience of location is among the most significant factors affecting hotel selection.

There isn't, however, sufficient research on the effect of time of day on sales from relevant industries. This might be because time of day is not a relevant factor for most service industries excluding the hair, beauty & restaurant industries.

Based on these findings two hypotheses were formulated:

*H1: Higher rating correlates to higher probability of sale*

*H2: Proximity to center correlates to higher probability of sale*

In the absence of relevant research concerning time of day no hypothesis on its effect can be made. The correlation of time of day with the probability of sale is however also studied.

### **4.3 Testing the Hypotheses**

The hypotheses were tested using R, an open source programming language for statistical computing. The data from available times and sold times were first combined in a new table to form the basis of the regression analysis. A dependent variable  $y$  was added to the table. Depending on whether a time slot is sold or not,  $y$  gets a value of 1 or 0, 1 meaning sold and 0 meaning not sold.

Two separate GLM models were tested. In the first model only rating, time of day and proximity to center were taken into account as explanatory variables. In the second model also weekday was added as an explanatory variable.

A binomial variance function with a logit link function was used in the model.

1.  $y \sim \text{rating} + \text{time of day} + \text{proximity to center}$
2.  $y \sim \text{rating} + \text{time of day} + \text{proximity to center} + \text{weekday}$

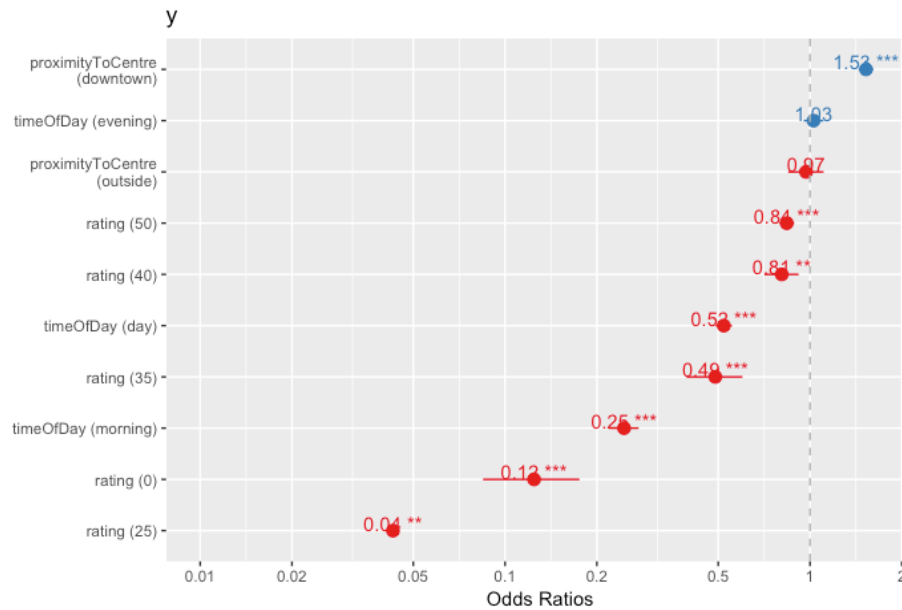
This kind of analysis reveals which factors have the most effect on whether a time slot is sold or not and if the effect is statistically significant.

After the GLM models were tested, ANOVA with chi-squared test was analyzed to study if the different factors actually helped to explain the dependent variable  $y$ .

The results were quite well aligned with the hypotheses, as can be seen from Picture 1. Proximity to center is the single most important factor affecting the probability of sale. This feels pretty logical, since downtown areas have the highest population density and in addition the greatest amount of workplaces. Also, the greatest amount of shopping possibilities, restaurants, bars, cafes and other attractions are also found in downtown areas. In other words, people are going there anyways, so it is suitable to also book e.g. a haircut from the same area. This is also in alignment with the findings of Rivers et al. (1991) and Ananth et al. (1992). It seems that as is the case with hotels, location is also a major factor affecting customers' choice of salon.

The effect of rating is not unambiguous. While having a rating of 4, 4.5 or 5 stars produced significantly better results than e.g. a rating of 2.5 stars, a rating of 4.5 stars yielded the best results. This calls for further research, since e.g. the number of ratings given wasn't considered in the model and might have an effect on the probability of sale also.

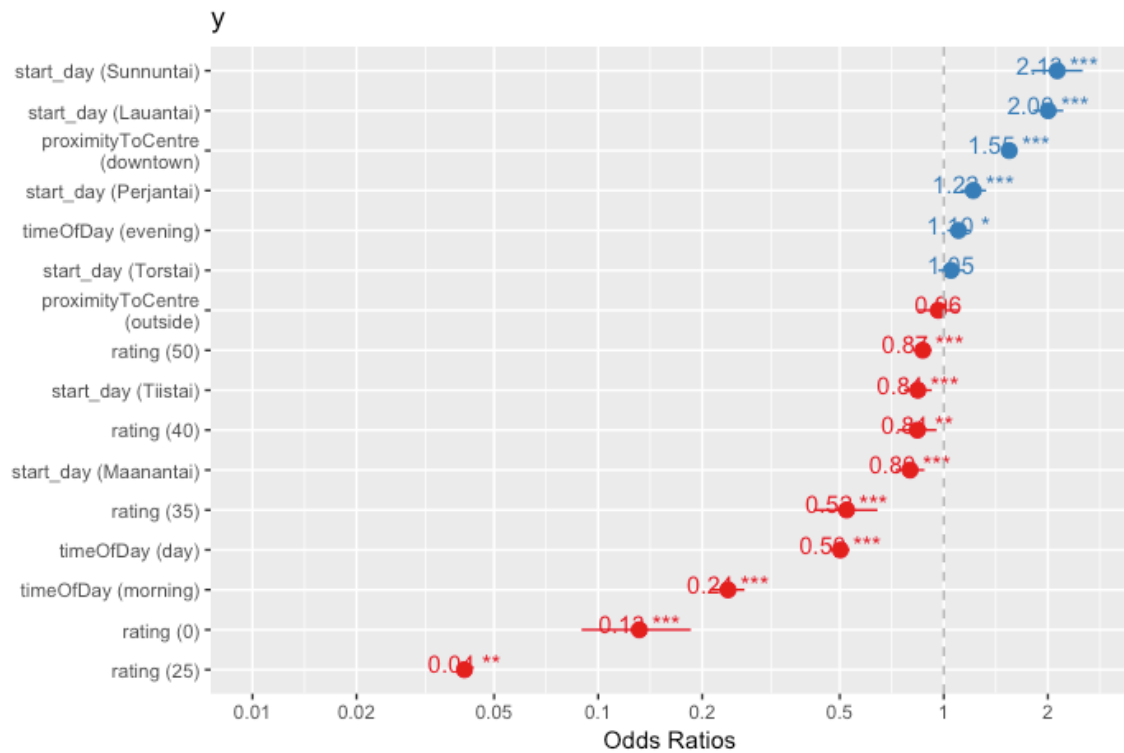
Time of day also had a significant effect on the probability of sale. Times starting in the afternoon and in the evening had twice the probability of being sold than times during the day and four times the probability of times starting in the morning. Results from GLM model 1 are shown in Picture 1.



Picture 1. The effect of different variables on the probability of sale, GLM model 1.

When the second model was tested it was found that the weekday actually has the biggest effect on the probability of sale. Sunday and Saturday have the highest probability of sale, two times as high as Wednesday. There might be two reasons for this. First of all, many if not most salons are closed or at least open a very limited time on weekends. This means that the amount of times available on weekends is quite low. Also, as can be seen from Picture 2, the weekdays are in complete reverse order in terms of likelihood of sale. This suggests that generally people don't like to use services provided by salons as much early in the week than they do when the weekend is getting near. Table 1 further illustrates the results from GLM model 2.





Picture 2. The effect of different variables on the probability of sale, GLM model 2.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.8725	-0.4914	-0.3994	-0.2949	3.1649

Coefficients:

	Estimate	StdError	ZValue	Pr(> z )
(Intercept)	-2.05956	0.04277	-48.155	<2e-16***
timeOfDay Day	-0.68901	0.03157	-21.867	<2e-16***
timeOfDay Evening	0.09833	0.03829	2.568	0.010225*
timeOfDay Morning	-1.43760	0.05687	-25.303	<2e-16***
rating50	-0.13998	0.02925	-4.786	1.70e-06***
rating40	-0.17590	0.06623	-2.656	0.007909**
rating0	-2.02824	0.18511	-10.957	<2e-16***
rating35	-0.64737	0.10780	-6.005	1.91e-09***
rating25	-3.19377	1.00424	-3.180	0.001474**
proximityToCenter Downtown	0.43573	0.02895	15.050	<2e-16***
proximityToCenter Outside	-0.03697	0.06860	-0.538	0.590471
start_day Saturday	0.69551	0.05144	13.520	<2e-16***
start_day Monday	-0.22487	0.04933	-4.558	5.16e-06***
start_day Friday	0.19667	0.04357	4.518	6.24e-06***
start_day Sunday	0.75599	0.08736	8.654	<2e-16***
start_day Tuesday	-0.17297	0.04729	-3.657	0.000255***
start_day Thursday	0.04830	0.04404	1.097	0.272770

Null Deviance:	42095 on 68444	Degrees of Freedom
Residual Deviance:	39883 on 68428	Degrees of Freedom
AIC	39917	

Table 1. Results from GLM model 2 as a table.

ANOVA with Chi-squared was also analyzed to find out if the addition of each variable improves the model significantly, i.e. if the variables help to explain the dependent variable significantly. As can be seen from Table 2, the residual deviance is initially 42095. The residual deviance decreases with the addition of each variable with a significant p-value, so it can be concluded that the variables (time of day, rating, proximity to center and weekday) each help to explain the dependent variable – whether the time is sold or not.

## Analysis of Deviance Table

Model: binomial

Response: y

Terms Added Sequentially First to Last

	Df	Deviance	Residual Df	Residual Dev	Pr(>Chi)
Null			68444	47095	
timeOfDay	3	1151.97	68441	40943	<2.2e-16***
rating	5	408.27	68436	40535	<2.2e-16***
proximityToCentre	2	741.50	68434	40793	<2.2e-16***
start_day	6	410.76	68428	39883	<2.2e-16***

Table 2. ANOVA table, GLM model 2.

## 5 Discussion

My research proves that proximity to center, time of day and rating all have a statistically significant correlation with the probability of sale. Additionally, weekday, which was originally not meant to be included as an explanatory variable had the largest effect on the probability of sale. The findings concerning proximity to center (location) and rating are in alignment with previous literature. (Rivers et al., 1991; Ananth et al. 1992; Ögut & Tas., 2012) The effect of rating does not, however, seem to be linear. In fact, a rating of 4.5 out of 5 stars seems to yield best results. There might be multiple reasons for this. Perhaps a rating of 4 stars or more is considered “good enough” by consumers and after that other factors affect the purchasing decision more than the rating. Also, written reviews were not taken into consideration as an explanatory variable. A salon with a 4-star rating might have more impressive written reviews than a salon with a 5-star rating. Furthermore, the number of reviews was also not taken into account in the model. It might be that a salon with a 4,5-star rating and huge total number of ratings is considered more appealing than a salon with a 5-star rating and only a small number of reviews.

In the case study different factors affecting the likelihood of sale are studied and tested. However, as discussed in the literature review section, dynamic pricing is essentially based on being able to estimate the future demand of the service/product as accurately as possible. While my research cannot be used as a base for fabricating a dynamic pricing model for hair and beauty services in the context of the Timma-marketplace, it

provides valuable insight on which factors are the most important ones affecting the probability of sale of a single time slot. It can be argued that this information is crucial when estimating demand for these services – when likelihood of sale is high, so is also demand. Of course, to develop a well-functioning demand-estimation model more factors would have to be taken into account.

## **5.1 Implications to Research**

No previous research about the sales of hair and beauty appointments via an electronic marketplace exists. My research suggests that location of the salon, time of day, consumer ratings and weekday all have a statistically significant effect on the probability of sale of an available appointment. This seems to be in alignment with previous research, although previous research from the hospitality industry only includes two of these factors, location and consumer ratings (Ögut & Tas, 2012; Rivers et al., 1991; Ananth et al., 1992).

My findings prove that in addition to previous studies from the hospitality industry, weekday and time of day affect the sales of hair and beauty appointments significantly. These might also be interesting factors to consider when studying the sales of other services, such as hotels, restaurants or golf tee times to name a few.

## **5.2 Implications to Practice**

My research reveals that weekday as a factor has the biggest effect on the probability of sale. Available times later in the week have a significantly higher likelihood of being sold than times early in the week. Moreover, times on Saturday and Sunday are sold twice as likely than times on Monday. Timma could use this information to help its salon customers sell more on the platform e.g. by encouraging salons to work longer hours on weekends. Also, as times in the afternoon and evening are have a significantly higher probability of sale than day times, salons should, if vacant, be closed during the day and remain open until later in the evening.

The demand for times early in the week seems to be lower than later on in the week. Salons might be able to sell more times for e.g. Monday and Tuesday by lowering prices specifically for those days. Similarly, times in the morning don't sell as easily as times in the evening or afternoon. Thus, lowering prices for times in the morning seems

sensible.

As discussed in the literature review, it is probably not feasible for individual salons or even salon chains to start formulating an algorithm to automate dynamic pricing. However, it seems feasible for Timma to start offering “Dynamic Pricing as a Service” for its salon customers. This could e.g. be priced as a flat monthly fee or value-based, if the increases in revenues for the salons could be reliably measured. The formulation of a dynamic pricing model or algorithm would require a deeper understanding of the different factors affecting the demand and remains an issue calling for further research.

### **5.3 Limitations and Future Research**

In the context of this study the effect of four explanatory variables on the probability of sale of a single time slot were studied. Although it seems that all of these factors affect the probability of sale and the effect is statistically significant, it is not possible to accurately forecast sales based on only these variables. To develop a deeper understanding of how to formulate a model for estimating demand for these services more variables would have to be taken into account. These include e.g. discount percentage, absolute price, number of customer reviews and how much in advance the booking was made. Moreover, it could be feasible to test the model individually for different services (e.g. haircut, cut & color, eyelash extensions) to develop an understanding about whether the factors affect the likelihood of sale differently for different services. Also, factors salons are not in control of, such as weather and date might also have an effect on the probability of sale.

The data studied includes only one city, Helsinki and one month, November 2017. It would be interesting to repeat the study with data from a longer time period and from various cities and different countries to find out whether the results from different cities and countries are in line with each other or if differences arise. It would be also interesting to see this study perhaps in a broader form repeated in some other service industry, such as restaurants to see if the results are in accordance with my study.

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